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The use of temporal metrics for land cover change detection at coarse spatial scales

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Abstract. Successful land cover change analysis requires selection of an appropriate set of variables for measuring and characterizing change. Coarse spatial resolution satellite sensors offer the advantage of frequent coverage of large areas and this facilitates the monitoring of surface processes. Fine spatial resolution satellite sensors provide reliable land cover information on a local basis. This work examines the ability of several temporal change metrics to detect land cover change in sub-Saharan Africa using remote sensing data collected at a coarse spatial resolution over 16 test sites for which fine spatial resolution data are available. We model change in the fine-resolution data as a function of the coarse spatial resolution metrics without regard to the type of change. Results indicate that coarse spatial resolution temporal metrics (i) relate in a statistically significant way to aggregate changes in land cover, (ii) relate more strongly to fine spatial resolution change metrics when including a measure of surface temperature instead of a vegetation index alone, and (iii) are most effective as land cover change indicators when various metrics are combined in multivariate models.

1. Introduction

The National Aeronautics and Space Administration (NASA) supports global change research via its Earth Observing System (EOS)—an extensive collection of satellite sensors which comprise part of NASA's Earth Science Enterprise (Asrar and Greenstone 1995). The Moderate Resolution Imaging Spectroradiometer (MODIS) is one of the key instruments for land sensing on the EOS platform, which is scheduled for launch in 1999. MODIS collects data in 36 spectral bands at 250, 500 and 1000 m spatial resolutions, while imaging the entire surface of the Earth every 1–2 days (Salomonson *et al.* 1989). One of the standard MODIS products will be the MODIS Land Cover Product which includes as one of its data layers a global 1 km land cover change database. Known as the Land Cover Change Parameter, this database is generated every three months from the most recent two years of MODIS data (Strahler *et al.* 1996).

The VEGETATION sensor onboard SPOT-4 (Système Pour l'Observation de la Terre), which was successfully launched in March 1998, also provides daily views of

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the globe at a spatial resolution of 1 km. These data likewise will be used to monitor land cover change, although with fewer spectral bands.

In order to characterize land cover change at regional to global scales, numerous issues must be addressed, including the problem of variable selection. Which of the available remote sensing data streams relate to land cover change? Are some variables more sensitive to certain types of changes than others? To what extent is it possible to characterize processes of land cover change based on coarse spatial resolution measures? How do measures of change scale up?

Several previous studies analysed time-series satellite data in order to develop intra-annual (Lloyd 1990, DeFries *et al.* 1995, Lobo *et al.* 1997, Nemani and Running 1997) and inter-annual (Reed *et al.* 1994) profiles of the condition of vegetation. These studies were mostly concerned with establishing phytophenological patterns within land cover classes. Patterns were represented by temporal metrics such as the mean annual Normalized Difference Vegetation Index (NDVI), maximum annual NDVI, etc. At present, few studies that use temporal metrics to detect land cover change directly have appeared in the literature (although see the work of Lambin and Ehrlich (1997)).

This research employed coarse spatial resolution temporal change metrics to model change estimated at 16 fine spatial resolution test sites located in sub-Saharan Africa. The intention was to gain a basic understanding of which variables should be most useful for land cover change analysis with MODIS and VEGETATION data once they become available. Our concept of land cover change includes both land cover conversions, i.e. the complete replacement of one cover type by another, and land cover modifications, i.e. more subtle changes that affect the character of the land cover without changing its overall classification. Land cover modifications are generally more prevalent than land cover conversions. A test site approach allows particular attention to areas for which land cover change dynamics are well understood. Although smaller in scope than a true global study, the sites contain a considerable variety of ecosystems influenced by variable climatic and anthropogenic conditions.

Since MODIS and VEGETATION data were not available at the time of this study, algorithm testing and development required the use of existing data such as those collected by the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA AVHRR). Spectrally, the MODIS and VEGETATION instruments are quite different from AVHRR, but AVHRR data provide analogues to two of the shortwave bands for MODIS and VEGETATION and two of the thermal bands for MODIS. Also, the AVHRR exhibits similarly fine temporal resolution to MODIS and VEGETATION, which is valuable for characterizing vegetation phenology. Additional remote sensing data sources included SPOT High Resolution Visible (HRV) and Landsat Thematic Mapper (TM) which provide data at fine spatial scales and are useful for gauging the ability of coarse-scale variables to detect and characterize land cover change.

2. Data

2.1. *Dataset*

The coarse spatial resolution database employed to generate the temporal metrics was derived from the Pathfinder AVHRR Land (PAL) dataset (James and Kalluri 1994). The dataset was constructed from 10-day maximum value NDVI composites at 8 km spatial resolution covering the years 1981–1994. Several other data layers were provided with this dataset, including the channel data associated with the maximum NDVI values. The NDVI and thermal channels were extracted from the full dataset as they provide complementary sources of information (Lambin and Ehrlich 1996, Nemani and Running 1997). An ancillary geolocation layer was also extracted.

Fine spatial resolution data consisted of six multi-temporal pairs of SPOT HRV, Landsat TM and Landsat Multispectral Scanner (MSS) scenes collected over areas where the land cover change dynamics were well understood at a local scale. Land cover characterizations of the scenes were provided through research projects at the Remote Sensing Laboratory of the University of Louvain in collaboration with teams operating in the field (e.g. Mertens and Lambin 1997). Additional information sources included personal communications with local experts in Africa.

2.2. *Preprocessing of fine spatial resolution data*

The fine-resolution data acquisitions underwent standard preprocessing including geometric registration and radiometric calibration. Subsets of the scenes were extracted in order to isolate specific areas of land cover change. Still, each subset, or test site, was large enough to be covered by several (2 to 9) adjacent PAL pixels in order to limit problems of misregistration at the coarser spatial resolution. As a result, some mixing of change processes was inevitable within the test sites. In particular, some sites were affected by a combination of regional-scale (often climate-driven) changes and localized anthropogenic changes. Table 1 gives a summary of the 16 subsites.

2.3. *Preprocessing of PAL data*

The NDVI data were recomposited to a 30-day time step from the original 10-day composites using maximum values in order to reduce cloud cover effects, and to produce a database similar in temporal character to that of the MODIS product design (Strahler *et al.* 1996). Additionally, surface temperature (T_s) images were generated from the thermal channels employing a split-window technique (Price 1984). The T_s data were also recomposited to a 30-day time step using maximum values, although it is of note that the thermal data were still dependent on the NDVI compositing process. Compositing the T_s data removes some part of the dynamic nature of the variable and retains mostly the seasonal pattern of temperature change. Thus, while the compositing of NDVI data mainly removes atmospheric contamination from time series, the compositing of T_s data also removes the information on surface dynamics which is related to daily variations in weather and soil moisture conditions. A cloud-screening algorithm based on the work of Saunders and Kriebel (1988) was applied to the monthly data in order to eliminate residual cloud-contaminated observations not removed by the compositing process. In addition to the NDVI and T_s time series, a time series of the T_s/NDVI ratio was computed, as this was shown to be an effective indicator of land cover change in earlier studies (Lambin and Ehrlich 1996, 1997). As in these previous studies, the arctangent of T_s/NDVI was computed to avoid nonlinear effects associated with a denominator that tends toward zero.

The last processing step was the location of the areas extracted from the fine-resolution scenes in the coarse spatial resolution data. This was achieved visually, without formal coregistration of the datasets as the PAL pixels were very large

Table 1. Subsite summaries.

Subsite #	Description	Loss (%)	Gain (%)
	Humid tropical forest in Cameroon		
1	Conversion of forest to small-scale agriculture	3.94	1.69
2	Conversion of forest to small-scale agriculture	2.46	0.25
3	Conversion of forest to small-scale agriculture	0.77	4.24
4	Forest modifications due to selective logging	0.00	4.02
	Dry forest and marigot in Senegal		
5	Conversion of agriculture to secondary forest	4.54	2.36
6	Flooding along marigots and expansion of wet rice cultivation in valleys	20.04	2.22
	Plains grassland in Kenya		
7	Drought recovery and conversion of grassland to small-scale agriculture	11.93	1.01
8	Grassland modifications due to drought recovery and localized burning or overgrazing (Loita plains)	19.58	0.50
	Dry savanna in Zambia		
9	Conversion of savanna to center-pivot agriculture	3.64	5.42
10	Conversion of savanna to subsistence agriculture	3.94	6.91
	Forest/savanna boundary in CAR		
11	Conversion of forest to small-scale agriculture	3.42	1.31
12	Forest modifications due to selective logging	0.49	2.04
13	No significant changes	0.04	2.08
	Plains grassland in Tanzania		
14	Grassland modifications due to drought recovery and localized overgrazing	18.31	0.04
15	Grassland modifications due to drought recovery and localized expansion of agriculture	17.20	0.91
16	No significant changes	0.01	2.98

relative to the fine-resolution pixels, and small geolocational discrepancies between the two databases of the order of a few pixels were essentially irrelevant.

3. Method

3.1. *Fine spatial resolution change metrics*

Fine spatial resolution estimates of land cover change were produced from NDVI difference images generated from the multi-temporal pairs (figure 1). These estimates required the setting of change thresholds for the difference images, which were derived with the assistance of University of Louvain personnel who had visited the sites. Detailed ground observations of vegetation cover, agricultural practices, wood exploitation activities, and land use intensity were assembled for each site. Landscape observations were collected along the main and secondary roads to cover the accessible parts of the study areas. Field observations were georeferenced using a global positioning system (GPS). These field data and available aerial photographs for the most remote areas were used for validation of the remote sensing based land cover change maps, and to support the interpretation of the statistical results. The output

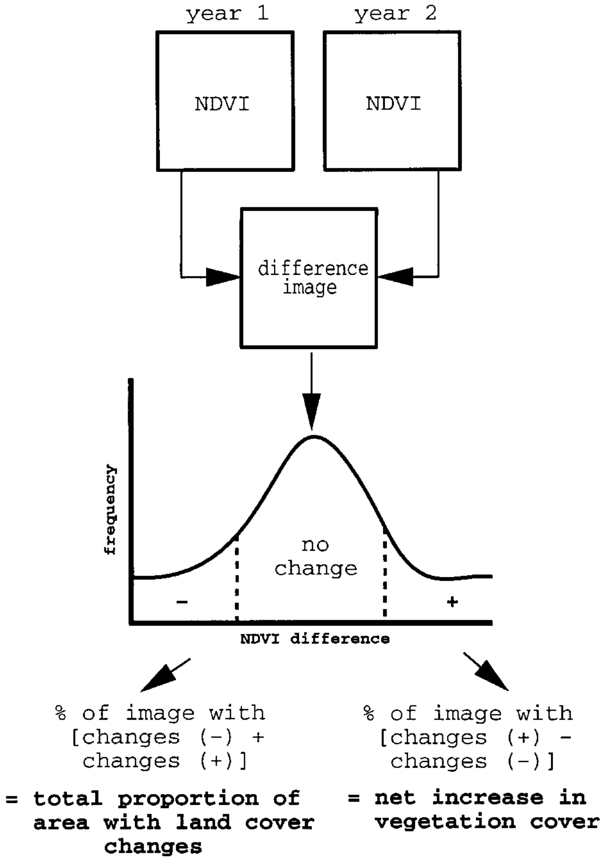


Figure 1. Computation of fine spatial resolution metrics.

statistics from this step represented estimates of the proportion of each subset which underwent land cover change between the two acquisition dates.

Two measures of change were of interest for each subset (figure 1). The first represented the proportion of pixels in the subset that underwent some form of land cover change, i.e. the sum of pixels undergoing a decrease and an increase in vegetative cover. A second measure represented the proportion of pixels in the subset that underwent a net gain in vegetative cover, i.e. the number of pixels undergoing an increase in vegetation cover minus the number of pixels undergoing a decrease in vegetation cover. The first measure illustrated the overall degree of change for a given subset. The second measure was more specific in its characterization of land cover change as it only detected net changes in one direction, and therefore assumed that the coarse-resolution change metrics would be sensitive to distinctions between positive and negative changes.

3.2. *Coarse spatial resolution temporal change metrics*

Computation of the coarse spatial resolution change metrics proceeded in four steps (figure 2). Firstly, the NDVI, T_s and T_s/NDVI ratio data were assembled into temporal signatures for each site, for each of the years for which high-resolution data were available. For some sites, there was no perfect coincidence between the

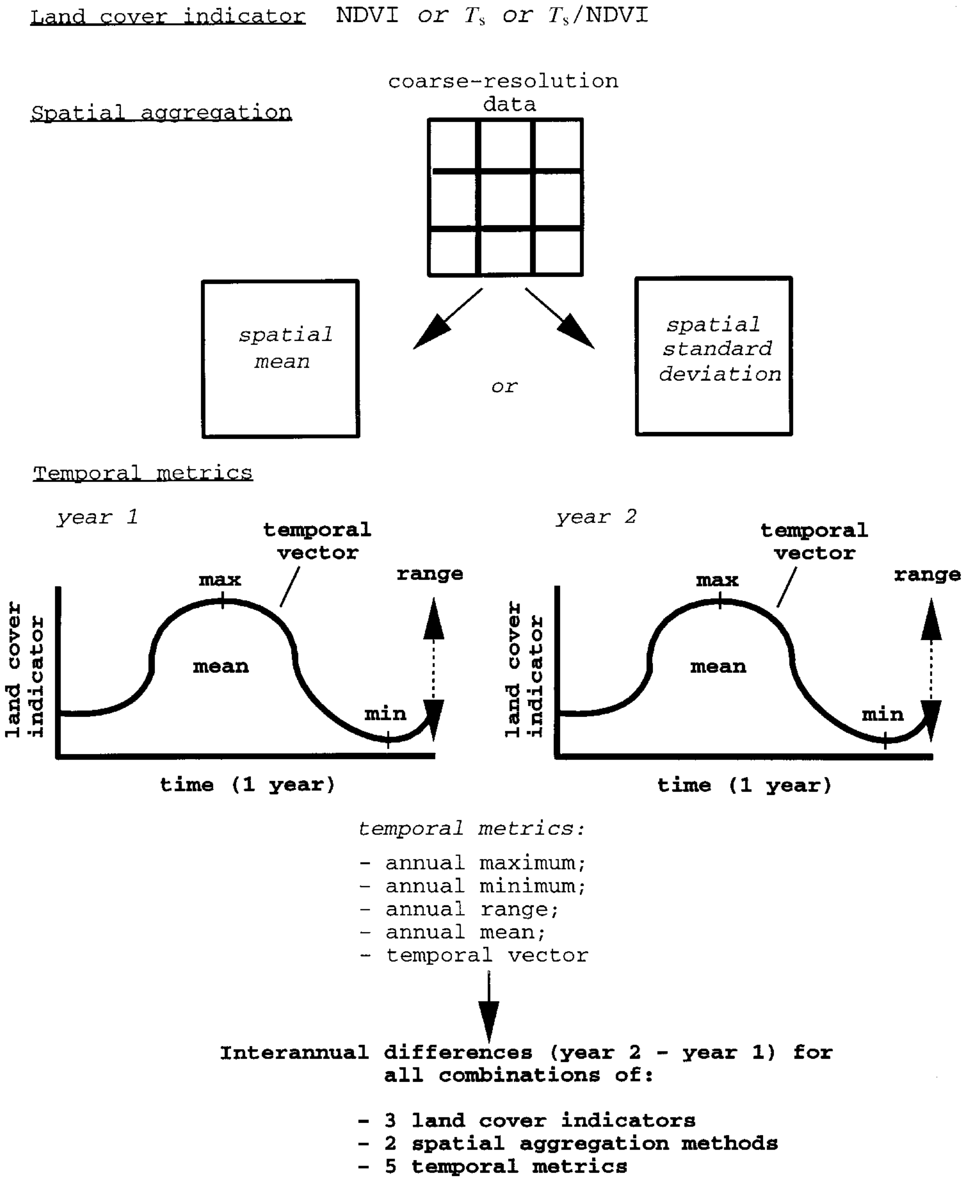


Figure 2. Computation of coarse spatial resolution metrics.

years for which both fine and coarse spatial resolution data were available. In that case, the closest year was taken, with a maximum of two years lag (with the exception of the Cameroon site, which used a 1973 image as a baseline).

Secondly, the 8 km pixels associated with each site were spatially aggregated over the subset for each month and each year. This spatial aggregation was conducted using two different methods, corresponding to different objectives: (i) by calculating the spatial mean for the 2 to 9 adjacent pixels which constituted a particular site—this identified the average temporal behaviour of the subset; and (ii) by calculating the spatial standard deviation for the 2 to 9 adjacent pixels of a site—this was intended to identify the seasonal changes in landscape spatial pattern. The concept of spatial pattern of a landscape includes, for example, the patch size distribution of residual forests, the location of agricultural plots in relation to natural vegetation, the shapes of fields or the number, type and configuration of landscape elements, i.e. their spatial heterogeneity. Landscape spatial pattern is seldom static due both to natural changes in vegetation and human intervention. It can therefore be used as an indicator of land cover change. Given the limited number of pixels per site however, the spatial standard deviation should be viewed here with some degree of caution.

Thirdly, metrics were calculated from the temporal signatures for the two years of aggregated data which were temporally coincident with the fine spatial resolution acquisitions. These metrics were (DeFries *et al.* 1995): annual mean, annual maximum, annual minimum and annual range (difference of maximum and minimum).

In the last step, once intra-annual metrics were extracted, it was possible to generate inter-annual land cover change metrics. The change metrics were calculated as the difference in the values of the given annual metrics for the two years of interest as:

$$\Delta = \text{Metric (year 2)} - \text{Metric (year 1)} \tag{1}$$

that is, the difference in annual mean, annual maximum, annual minimum and annual range. In addition to these synthetic change metrics, a more thorough measure of inter-annual change between two seasonal trajectories of a given land cover change indicator was represented by the magnitude of the multi-temporal change vector. This measure, which was described and tested elsewhere previously (Lambin and Strahler 1994), was computed as:

$$\mathbf{c}(i) = \mathbf{p}(i, y) - \mathbf{p}(i, z) \tag{2}$$

where $\mathbf{c}(i)$ is the change vector for pixel i between the years y and z and $\mathbf{p}(i, y)$ is the multi-temporal vector for pixel i and the year y:

$$\mathbf{p}(i, y) = \begin{vmatrix} I(t_1) \\ I(t_2) \\ \cdots \\ I(t_n) \end{vmatrix} \tag{3}$$

where I are the values of the indicator under consideration for pixel i at the time periods t_1 to t_n, n being the number of time dimensions. The magnitude of the change vector, $|\mathbf{c}|$, measures the intensity of the change in land cover.

These five change metrics were computed for all combinations of land cover indicators and spatial aggregation methods. Thus, the total number of coarse-resolution change metrics generated for each site was thirty (given three land cover indicators, two aggregation methods and five temporal metrics).

3.3. *Statistical relationships between fine and coarse spatial resolution change metrics*

Once the measures of land cover change were estimated for each test site, and each coarse-resolution temporal change metric was generated, the next step was to test the statistical strength of the relationships between these measures using statistical models. This testing was performed without regard to land cover change type. That is, changes due to interannual climatic variability were grouped with anthropogenic changes and land cover conversions were grouped with land cover modifications.

The first approach was univariate linear regression. For each regression, the dependent variable represented one of the fine-resolution estimates of land cover change (total change or net increase in vegetative cover), and the independent variable was one of the temporal change metrics. This model should be useful for characterizing net increase, which is a monotonic function of any coarse-resolution metric. A second approach was to fit a quadratic model to the data as some of the relationships between the fine-resolution change and the coarse-resolution metrics appeared to be nonlinear. Also, the quadratic should be better suited to modelling total change as it is able to account for nonlinear mixing of gains and losses at fine resolution.

Additionally, it was of interest to determine whether combinations of metrics produced stronger relationships with the fine spatial resolution data than univariate models. Employing all of the metrics in a multiple regression did not seem particularly useful owing to the likelihood of intercorrelations between metrics. Therefore, a third approach was to relate the metrics to fine-scale change via a stepwise regression.

4. Results

Intuitively, the coarse-scale metrics should be helpful for detecting certain types of land cover change and less useful for other sorts. Change vectors respond to aggregate changes in remote sensing data, and should therefore relate best to the total change at fine spatial resolution. The maximum, mean, minimum and range should all be related to net gain of vegetation.

4.1. *Univariate linear regressions*

Table 2 shows the results of the strongest univariate linear relationships between each of the fine spatial resolution estimates of change and the temporal metrics. The most interesting outcome is the better statistical performance in detecting changes with T_s or T_s/NDVI than the NDVI alone. Only one NDVI metric is significantly

Table 2. Univariate linear relationships between change metrics and fine-resolution estimates of change ($n = 16$).

Change metric	Spatial aggregation	Root mean squared error	Adjusted R^2
Total change			
T_s/NDVI ratio, difference of maximum values	mean	0.042	0.64 ($p < 0.0001$)
T_s, change vector magnitude	mean	0.042	0.64 ($p < 0.0001$)
Net vegetation gain			
T_s, difference of mean values	mean	0.057	0.57 ($p < 0.0004$)
T_s/NDVI ratio, difference of mean values	mean	0.060	0.52 ($p < 0.0009$)

related to either of the fine-resolution change estimates, but its associated R^2 is quite low (not tabled). Additionally, none of the most useful metrics are based on the spatial standard deviation.

For the relationships with total fine-resolution change, the difference of the maximum T_s/NDVI ratio values and the change vector magnitude of T_s exhibit the highest R^2 statistics (see upper half of table 2). Figure 3 shows the associated scatter plots along with the fitted regression lines. The difference of the maximum T_s/NDVI ratio is inversely proportional to overall change in land cover (figure 3(*a*)). This makes sense because a change in the maximum value of the T_s/NDVI ratio (high temperature with low vegetative cover) indicates that the lowest level of vegetative cover through a seasonal cycle has changed between the years of interest. The T_s change vector magnitude is independent of change direction, and thus should be positively correlated to the total fine-resolution change, as is shown in figure 3(*b*).

As shown in the lower half of table 2, the strongest relationships with net vegetation gain at fine resolution are the difference of mean T_s and the difference of the mean T_s/NDVI ratio, although neither of these relationships is as strong as those found for total fine-resolution change. Figure 4 shows the associated scatter plots along with the fitted regression lines. The difference of mean T_s reflects the inter-annual variability of surface moisture status (Carlson *et al.* 1990), which one would expect to be inversely correlated with vegetation gain (Goward *et al.* 1985), but it is not (figure 4(*a*)). The difference of the mean T_s/NDVI ratio is proportional to net gain of vegetation (figure 4(*b*)), which is also apparently counterintuitive because this indicator measures average increase in temperature with a simultaneous decrease in greenness.

Sites 6, 8, 14 and 15 display a distinct behaviour in these relationships compared to the other sites (note that the same is true for all of the other relationships with net vegetation increase examined below). For site 6, which encompasses several valley bottoms and marigots in Basse Casamance, there was a significant increase in rainfall between the two years for which the high resolution data were collected (1986 and 1994) (Linares 1995). This has led to an increase in surface moisture. The increase in water level and valley floodings has caused a decrease in vegetation cover in these locations. This process was accelerated by vegetation clearings in valleys for wet rice cultivation (Linares 1995).

The other sites (8, 14 and 15) are all part of the Serengeti Ecological Unit. This region was affected by a severe drought in 1984 with persistent effects on vegetation, and a slow and progressive recovery of rainfall over the next few years (including 1985 and 1987 which are the years of acquisition of the first set of high-resolution images). This was followed by wetter conditions until the year of acquisition of the second set of high-resolution images (1995). In addition, these three east African sites were affected by diverse local-scale changes, such as increased fire frequency, agricultural expansion and increased grazing pressures. The processes leading to local-scale changes were all spurred by the improved climatic conditions measured at the regional scale, in addition to being driven by demographic pressures and changes in land use.

Thus, all four sites were subjected to a combination of regional-scale, climate-driven land cover modifications and local-scale, anthropogenic land cover conversions. The regional-scale changes at all four sites were associated with higher surface moisture, and therefore a decrease in T_s. The local-scale changes at all four sites were associated with localized decreases in vegetation cover, and therefore decreases

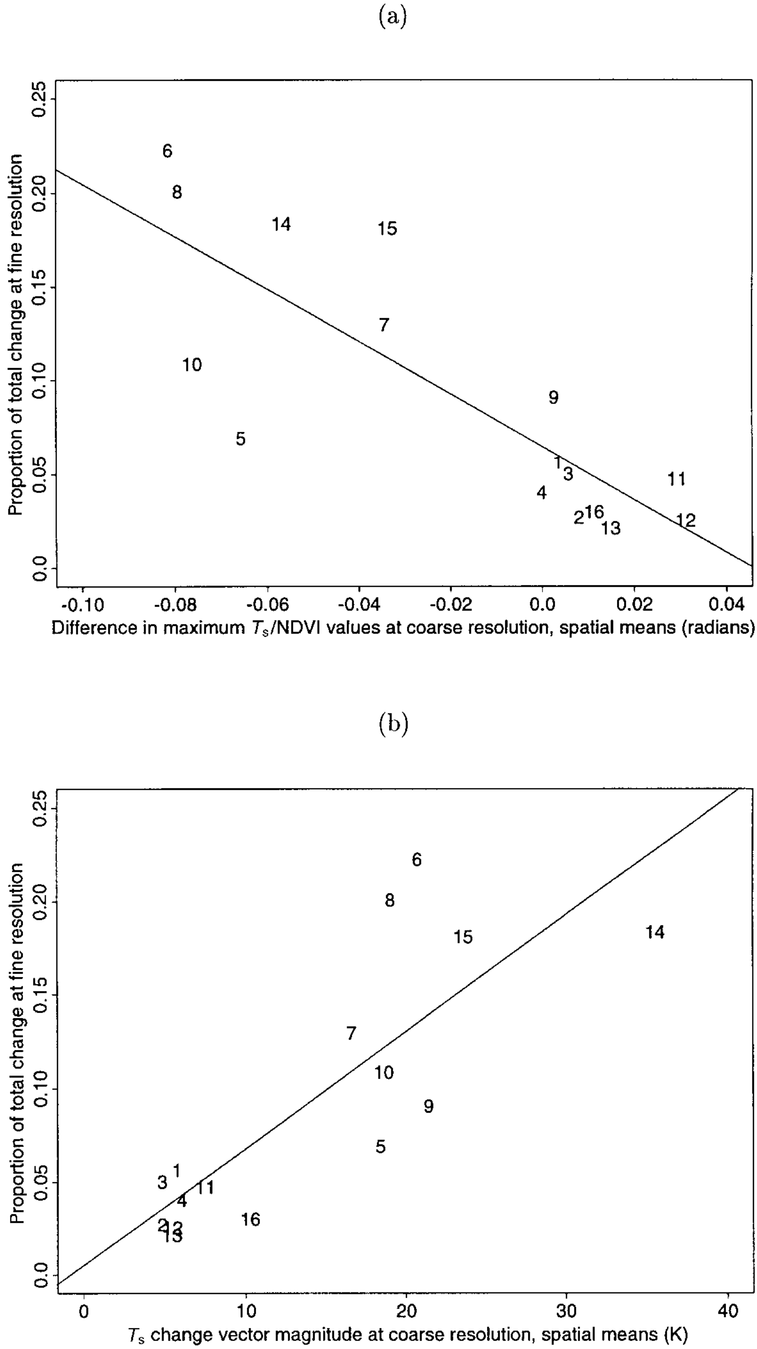
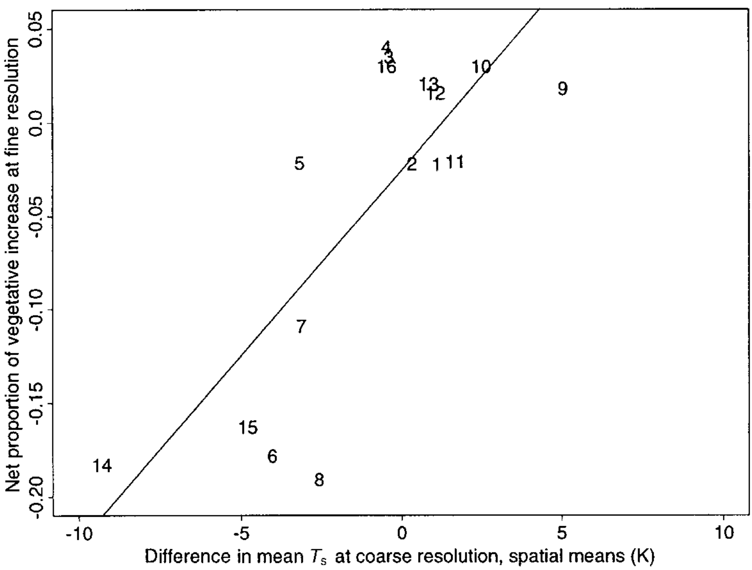


Figure 3. Best relationships for measuring total change, univariate linear regression. Data points are plotted by site number as listed in table 1.

in the NDVI. It is very likely that primarily regional-scale processes were detected at the coarse spatial resolution (decrease in T_s and T_s/NDVI), while at fine spatial resolution, the local-scale changes in vegetation cover dominated the change detected

(a)



(b)

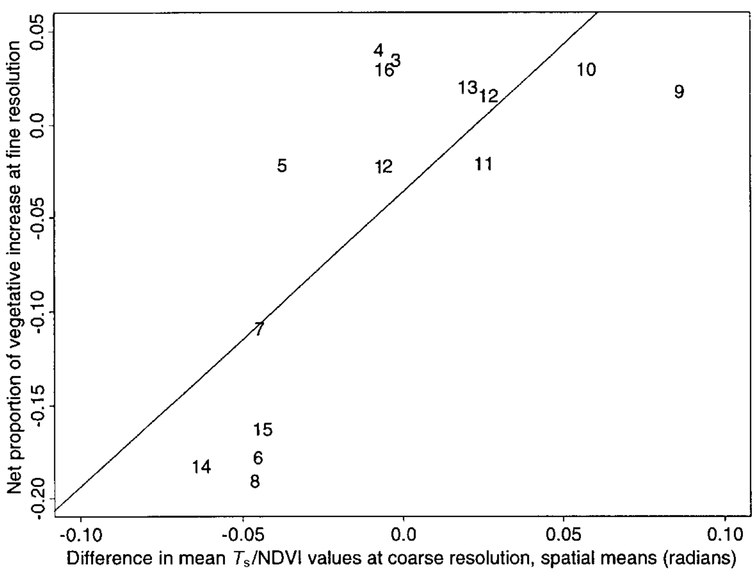


Figure 4. Best relationships for measuring net vegetative increase, univariate linear regression. Data points are plotted by site number as listed in table 1.

(net vegetation loss). This explains why a negative difference in mean or maximum T_s (or T_s/NDVI)—i.e. a decrease in T_s between year 1 and year 2—was measured at the coarse spatial resolution, while at the same time, a high value of vegetation loss (negative vegetation increase) between year 1 and year 2 was measured at the fine spatial resolution for these four sites.

The fact that different land cover change processes might be measured at the two spatial resolutions renders the interpretation of the statistical results less valid, unless there is a causal link between the regional-scale and local-scale land cover change processes. This is thought to be the case here for all four sites, in that the increase in rainfall between the two years promotes a decrease in vegetation cover in the valleys (only in Casamance), expansion of agriculture due to the increase in moisture availability, more biomass burning due to the increase in end-of-season standing biomass and increased grazing pressure due to the restoration of herds following the drought.

4.2. *Quadratic models*

Another means of relating the temporal metrics to fine-scale change is to fit simple quadratic models, i.e. no interaction terms, to each of the coarse spatial resolution metrics. The chief reason for employing quadratic models is to examine several coarse-scale metrics which do not appear to be linearly related to fine-scale change. The T_s/NDVI ratio metrics tend to be most problematic in this regard. Also, as stated previously, the quadratic model may aid in accounting for nonlinear mixing of vegetative gain and loss as estimated from the fine-resolution data.

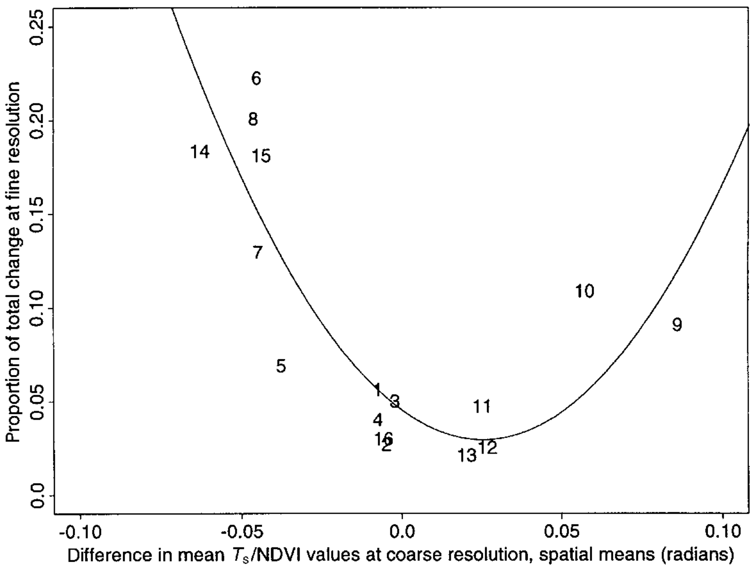
For the relationship with total fine-resolution change, the difference of the mean T_s/NDVI ratio exhibits the highest R^2 statistic. This metric measures a sort of annually integrated change in surface characteristics. Figure 5(*a*) shows the associated scatterplot and model fit, which indicate that this metric increases in absolute value as total fine-resolution change increases, as one would expect. The metric with the next highest R^2, the T_s change vector magnitude, appears to be a reasonable model based on its R^2 alone (0.65), but the second-order term does not add significantly to the model, and artificially inflates the R^2. Consequently, this metric is not particularly effective in the quadratic model. The T_s/NDVI ratio change vector magnitude is the next best of the quadratic models with total fine-resolution change where both model terms are significant (the associated R^2 is 0.59). Figure 5(*b*), which shows the associated plot and model fit, indicates that the T_s/NDVI ratio change vector magnitude increases as total fine-resolution change increases, although it appears to saturate near a total change proportion of 0.15.

The best relationship with net vegetation gain at fine spatial resolution is the difference in the mean T_s/NDVI ratio. Both terms are significant in this model, which is plotted in figure 6. The difference in mean T_s/NDVI ratio appears to saturate near a net increase proportion of 0.05. The metric with the next highest R^2 is the difference in mean T_s. In this case, the second-order term is not significant, so the metric is not effective in the quadratic model.

Note that some of the quadratic functions are not monotonic over the domain of the associated coarse-resolution metric. In those cases, there are two possible values of coarse-resolution metrics for a single value of the fine-resolution metrics and the model cannot be inverted. The relationship shown in figure 5(*b*) could be problematic in this regard.

The results of the best overall quadratic relationships between the fine-resolution estimates of change and the temporal metrics are summarized in table 3. Again,

(a)



(b)

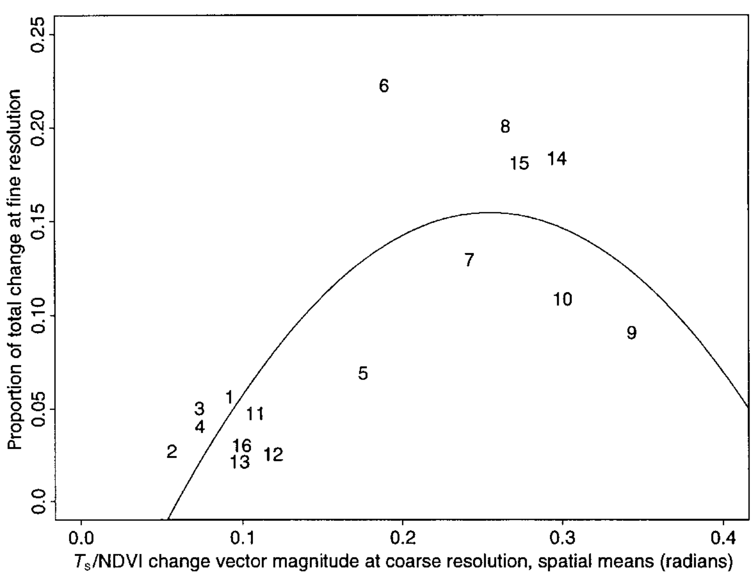


Figure 5. Best relationships for measuring total change, quadratic model. Data points are plotted by site number as listed in table 1.

T_s and the T_s/NDVI ratio are more strongly related to change than the NDVI alone (no statistically significant metrics), and the most useful metrics are based on spatial means.

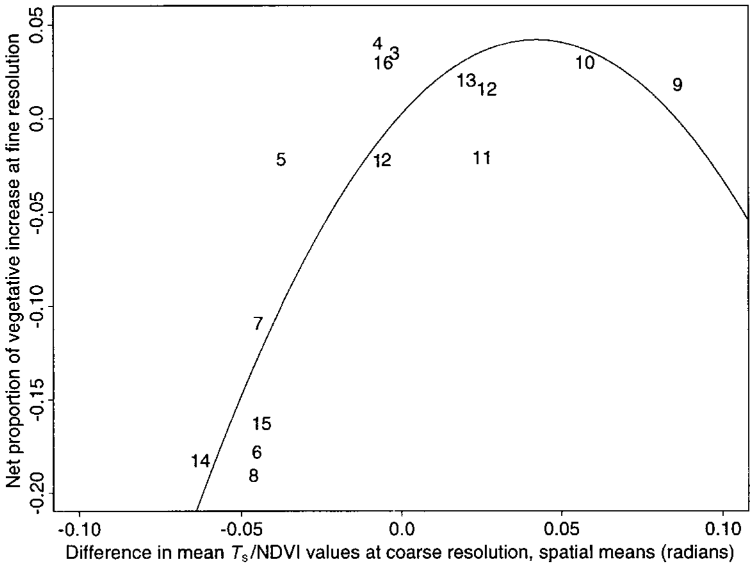


Figure 6. Best relationships for measuring net vegetative increase, quadratic model. Data points are plotted by site number as listed in table 1.

4.3. *Stepwise regressions*

The aim of employing stepwise regression is to determine whether combinations of temporal metrics relate better to fine-scale change than do the univariate linear or quadratic models. Clearly, intercorrelation between the coarse-scale metrics is difficult to avoid, but those variables which complement one another are of interest. Table 4 shows the best combinations for each fine-resolution change estimate, in order of decreasing contribution to the multivariate R^2. The selected variables consist mainly of metrics based on spatial means, although both of the stepwise models contain metrics based on spatial standard deviations. The R^2 statistics for these multivariate models are noticeably greater than those achieved with univariate linear regression. For the quadratic models, the stepwise regression models are better for total change, but not for net gain.

The estimates of total fine-resolution change are predicted best by combining into a single model the difference in maximum T_s/NDVI ratio based on spatial

Table 3. Quadratic relationships between change metrics and fine-resolution estimates of change ($n = 16$).

Change metric	Spatial aggregation	Root mean squared error	Adjusted R^2
Total change			
T_s/NDVI ratio, difference of mean values	mean	0.038	0.70 ($p < 0.0002$)
T_s/NDVI ratio, change vector magnitude	mean	0.044	0.59 ($p < 0.0004$)
Net vegetation gain			
T_s/NDVI ratio, difference of mean values	mean	0.043	0.75 ($p < 0.0001$)

Table 4. Stepwise linear regressions between change metrics and fine-resolution estimates of change ($n = 16$).

Change metric	Spatial aggregation	Root mean squared error	Adjusted R^2
Total change			
T_s/NDVI ratio, difference of maximum values	mean	0.026	0.86
T_s/NDVI ratio, difference of mean values	std. dev.	($p < 0.0001$)	
T_s, change vector magnitude	mean		
Net vegetation gain			
T_s, difference of mean values	mean	0.042	0.77
T_s, difference of ranges	std. dev.	($p < 0.0001$)	

means, the difference in mean T_s/NDVI ratio based on spatial standard deviations and the T_s change vector magnitude based on spatial means. Due to their strong relationship to total change in the univariate linear analysis, selection of the first and third variables is unsurprising. It is of note, however, that their information content is complementary. The second metric, the difference in mean T_s/NDVI ratio based on spatial standard deviations, is not strongly related to total change with univariate linear regression, but it adds significantly to the multivariate model. The sign of its relationship with total change at fine spatial resolution is negative, indicating that as total change increases, the mean annual spatial heterogeneity of the T_s/NDVI ratio decreases. For some change processes this makes sense, for others it does not. In fact, Estreguil and Lambin (1996) have demonstrated that the relationship between the level of landscape disturbance and the spatial heterogeneity of a landscape has an inverted-U shape, i.e. landscape heterogeneity first increases with initial levels of disturbances (due to landscape fragmentation) and then decreases with more severe disturbances (leading to a homogeneous, completely cleared landscape).

For the relationship with net vegetation gain at fine spatial resolution, the metrics selected by stepwise regression are the difference in mean T_s based on spatial means and the difference in T_s range based on spatial standard deviations. As with the univariate linear regression model, the difference in T_s mean is strongly related to fine-resolution vegetation gain. The difference in T_s range based on spatial standard deviations is not strongly related to fine-scale vegetation gain in the univariate linear case, but it adds significantly to the multivariate model. This metric may be useful for detecting subtle vegetation changes because it captures the range in annual spatial heterogeneity as measured by the T_s/NDVI ratio. The sign of this relationship is positive.

5. Discussion

One potential source of error in this study is the use of the fine-resolution measures of change as 'truth'. Although based on detailed field assessments, errors of omission or commission may have been introduced when identifying land cover change in the Landsat and SPOT images. Due to time constraints, it was not possible to perform a formal accuracy assessment, but the quality of the field data is such that the change estimates may be considered reasonably reliable nonetheless.

Another point that should be stressed is that the fine-resolution and coarse-resolution change metrics can measure different land cover change processes.

Regional-scale processes may not be detectable at a local scale and vice versa. If the processes are unrelated, the statistical relationships cannot be modelled by the techniques presented here, and more complicated statistical approaches should be applied. If, however, a causal relationship exists between the two, as illustrated in the results of this study, the methodology presented here is valid. In this study, we suspect that different processes of change are measured at the fine and coarse spatial resolutions only when employing the fine resolution change metric which measures the net increase in vegetation. This is not the case with a measure of the total change taking place. The latter metric is more of a crude, aggregate measure of change, which is therefore more likely to be related to the changes measured at coarse spatial resolution.

Not only can fine-resolution and coarse-resolution change metrics measure different processes, but the different coarse-resolution land cover indicators can respond to different types of land cover change. For example, T_s and the T_s/NDVI ratio are in all cases more strongly related to the fine-resolution estimates of change than the NDVI alone. As all of the change processes have been grouped in this study, one possible explanation is that the variability of NDVI cannot be generalized in terms of how it relates to specific land cover types and their conversions, but T_s and the T_s/NDVI ratio may be better suited to measuring change in general, regardless of type. More specifically, the NDVI could be related more closely to individual conversion processes while T_s and the T_s/NDVI are more sensitive to climate-driven land cover modifications which better lend themselves to general descriptions of change.

Also of note is the inherent utility of the statistical models employed in this research to describe fine-resolution change. Net gain is a quantity that should exhibit linear behaviour across the domain of a given coarse-resolution metric as it is a linear function of any coarse-resolution metric. Total change may be best described by a higher order function (such as a quadratic) that is able to model a nonlinear mixture of losses and gains at fine resolution, as suggested by figure 5.

Lastly, it is important to bear in mind that the sample size and geographic coverage of this study are limited. Just 16 test sites from sub-Saharan Africa were used to fit the univariate linear, quadratic and stepwise models. Clearly, caution must be exercised when extrapolating these findings to other experiments or environments. The current research is designed to be an exploratory analysis, and in the absence of actual MODIS or VEGETATION data, a degree of uncertainty is unavoidable.

6. Conclusions

Several conclusions may be drawn from the current research. First, relationships between fine-scale change and coarse spatial resolution metrics are non-random. This is encouraging given the fact that the PAL dataset is spatially much coarser than what will be available from MODIS or VEGETATION, and the radiometric quality of these data sources will greatly exceed that of AVHRR data.

Secondly, the T_s and T_s/NDVI ratio metrics are statistically better at detecting changes than the NDVI metric alone. This confirms the importance of T_s data as being a complementary source of information (at the very least) to NDVI data.

Thirdly, the results of the stepwise regressions clearly show that multivariate combinations of the temporal metrics represent statistical and substantive improvements over the univariate linear or quadratic models. The R^2 statistics are consistently highest for the multiple regressions. Additionally, the variables selected by the stepwise procedure complement one another, and in fact draw on information from the temporal, spectral and (possibly) spatial domains.

We are fully aware of the numerous limitations of AVHRR time-series data and of the artefacts generated due to their coarse spatial resolution. They are, however, the only data currently available for use in an experiment such as this one. The statistically significant relationships found in this study suggest that the implementation of a land cover change product based on 1 km resolution MODIS or VEGETATION data will succesfully detect a range of land cover change processes of interest for global change studies.

In this study, three sources of variation in the change metrics were considered simultaneously: differences in spatial resolution, in temporal resolution and in land cover indicator. Future work will examine the impact on change metrics of each source of variation independently, by keeping the other two constant. This will allow us to conduct a more explicit comparison of the information provided by fine-resolution 'snapshots' and coarse-resolution continuous time-series data.

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